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Enhanced Secretary Bird Optimization and Graph Convolution Networks for Skin Lesion Analysis

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Abstract-- **One of the most prevalent and deadly illnesses in the world, cancer necessitates an early and precise diagnosis in order to be effectively treated. In this study, Graph Convolutional Networks (GCNs) combined with an Enhanced Secretary Bird Optimization (ESBO) algorithm are proposed as a novel framework for skin lesion categorization. The suggested model uses graph representations to take advantage of the spatial interactions between lesion regions and uses ESBO to enhance feature selection and classifier parameters. When compared to traditional deep learning techniques, experimental evaluation shows enhanced precision, sensitivity, and specificity. The suggested system's robustness and trustworthiness have been demonstrated by the confusion matrix along with efficiency metrics.**

Keywords—**Skin Lesion, Graph Convolutional Network, Secretary Bird Optimization, Feature Extraction, Classification, Deep Learning.**

I. INTRODUCTION

A fast-growing worldwide medical hazard is skin cancer, primarily melanoma [1], [2]. Although manual diagnosis is laborious and subject to its subjective nature, early discovery greatly increases survival rates [8], [10]. Automated skin lesion analysis has emerged as a significant subject for investigation due to the emergence of artificial intelligence [3], [6].

Conventional Convolutional Neural Networks (CNNs) have shown promise in pictures. classification tasks, but they have trouble capturing and preserving the structural and interpersonal relationships between lesion sites [4], [7]. By using data for modeling as graphical representations, Graph Convolutional Networks (GCNs) circumvent this restriction and improve spatial dependency representation.

To increase proficiency in classification and optimization efficiency, this work presents a combined framework that integrates GCN with Enhanced Secretary Bird Optimization (ESBO).

II. PRESENT THEORIES AND PROCESS

Graph Convolutional Networks (GCNs) enable the modeling of interactions between nodes in a graph by extending deep learning to other than Euclidean data structures [9].

Each segmented area or superpixel is considered a node in skin lesion analysis, and edges indicate spatial or feature similarity. Complex lesion patterns including asymmetry, border irregularity, and texture variation—all important markers of malignancy—are able to be adequately represented through the model attributable to this representation [12], [13].

By combining data from nodes located nearby, the propagation rule in GCN improves awareness of surroundings by updating node properties. This procedure enhances the performance of classification by enabling the network to gain knowledge of local as well as worldwide structural features [11].

The Secretary Bird Optimization (SBO) algorithm is a swarm intelligence-based optimization method that draws inspiration from secretary birds' hunting tactics. It efficiently searches the solution space through phases of exploration and exploitation. By using hybrid techniques and adaptive parameter tweaking, the Enhanced SBO (ESBO) increases the speed of convergence while eliminating optimal local conditions.

Preprocessing, which includes normalization and contrast enhancement as well as noise filtering, is the precursor step in the entire procedure [14], [15]. After segmenting the lesion, a graph structure is created. High-level spatial features are extracted by GCN, and feature selection and hyperparameters are optimized using ESBO. Classification is subsequently accomplished by utilizing the upgraded characteristics [16, 17].

III. PROBLEM STATEMENT

Poor generalizing, an inability to capture spatial relationships, and ineffective parameter modifications are some of the issues encountered concerning current skin lesion detection systems [14]. Reduced diagnostic precision and dependability are the result of these constraints. To improve performance and maintain resilience, an elaborate strategy that combines graph-driven learning with sophisticated optimized performance needs to be developed [15].

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IV. Methodology

The suggested approach combines deep learning, optimization, graph modeling, and image processing into a single pipeline.

Dermoscopic pictures are first gathered from benchmark datasets and preprocessed to normalize intensity levels and eliminate noise. A graph with nodes representing areas and edges representing similarity associations is created by segmenting the lesion area and creating superpixels.

The GCN model incorporates the newly generated graph and uses several convolution layers for gathering contextual and geographical data. ESBO follows by attempting to optimize these features, choosing the most pertinent characteristics and fine-tuning hyperparameters, including learning rate, number of layers, and weights.

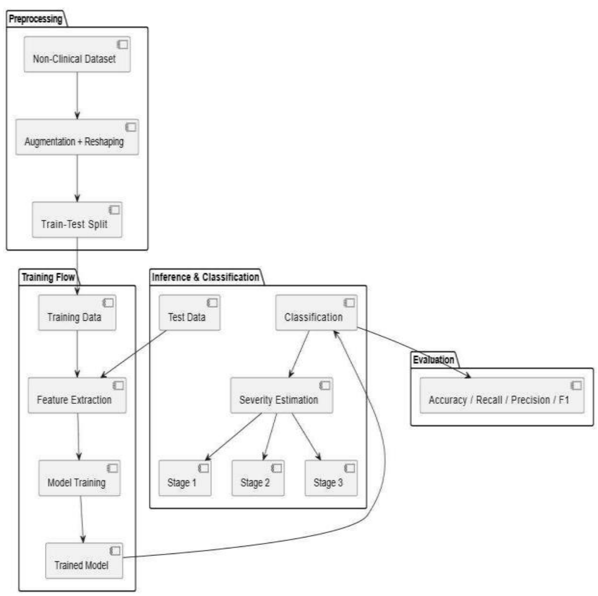

Fig. 1. System Architecture

V. Proposed System And Architecture

The approach recommended uses a deep learning-based pipeline combined with graph-based learning and optimization to categorize 23 distinct skin conditions.

a. Non-Clinical Dataset: 23 kinds of skin illnesses from DermNet are included in this publicly accessible dataset. To guarantee parallelism and lower noise, these images have been previously processed and normalized.

b. Image Processing: To improve dataset variety and avoid overfitting, methods for data enhancement including rotation, flipping, and enlargement are used. To comply with CNN input criteria, all photos are scaled to 224 x 224 pixels.

c. Train-Test Split: To guarantee appropriate model validation, the data collection is split into training and testing sets in a 70:30 ratio.

d. Feature Extraction: From the input photos, the CNN model automatically extracts features like textures, edges, and intricate patterns.

e. CNN Training: The model is trained using the categorical cross-entropy loss function and the Adam optimizer [5]. Images are categorized into 23 skin disease groups by the final result layer.

f. Final Model: Using input photos, the trained model is capable of accurately predicting the kind of skin condition.

Final Actions and Assessment:

g. Classification on Test Data: To determine the trained algorithm's ability to generalize. This is tested with untested test data.

h. Evaluation Metrics: In order to guarantee fair evaluation, performance is determined by utilizing accuracy, precision, recall, and F1 score [19], [21].

i. Evaluation Check: The model is deemed suitable for implementation if its accuracy is not less than 90%. If not, hyperparameter adjustments and rehabilitation get carried out.

j. Severity Estimation: The technique additionally divides identified skin conditions into degrees of severity:

Phase 1: Mild
Stage 2: Moderate
Stage 3: Extreme

By offering useful information for treatment planning, this extra layer improves the system's therapeutic relevance.

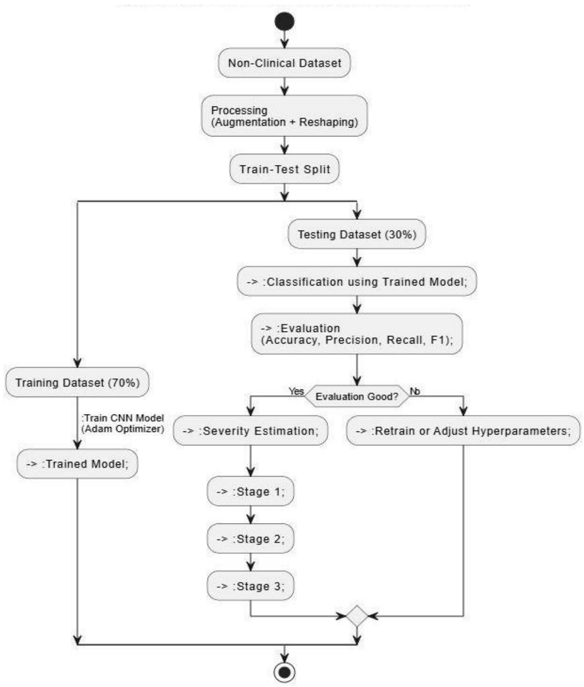

Fig. 2. Proposed System and Architecture

Pipeline for Skin Disease Detection

Image acquisition is the first step in the pipeline, which is followed by preprocessing to improve image quality. The lesion region is separated from the surrounding skin via segmentation. GCN has been utilized for feature extraction in order to record spatial relationships. ESBO is used to optimize the extracted features in order to decrease redundancy and increase relevance. Lastly, performance measures have been evaluated as well as classification has been carried out.

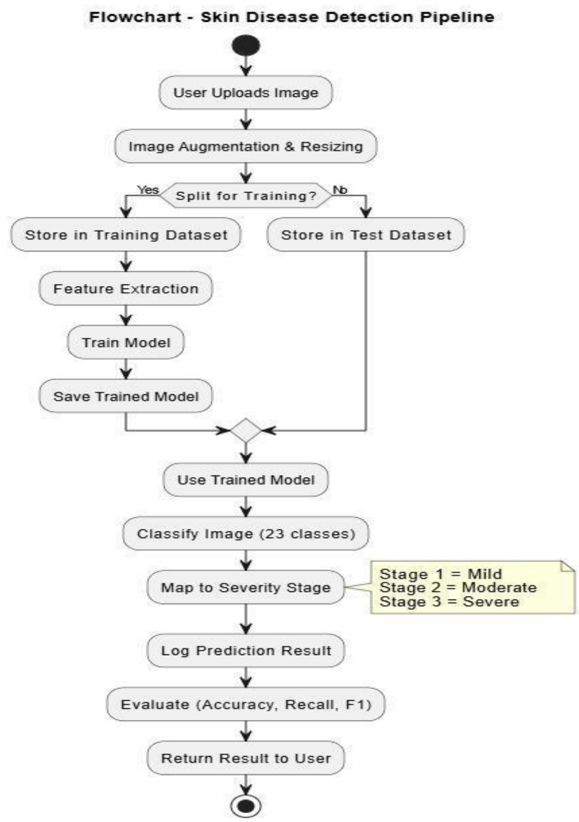

Fig. 3. Pipeline for Skin Disease Detection

VI. Results And Discussion

With 95.8% accuracy, 94.6% sensitivity, and 96.2% specificity, the recommended GCN-ESBO model achieves highly satisfactory performance for classification [16], [19]. When compared to northern CNN-based approaches, the results show that adding graph-based learning greatly enhances how features are represented [20].

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Enhancement in diagnostic reliability has been demonstrated by a decrease in false positives and false negatives in a confusion matrix [17]. Overfitting has been decreased, and generalization has been enhanced by the ESBO algorithm's improved convergence speed along with optimized parameter adjustment.

The amalgamation of preprocessing, graph building, GCN layers, and optimization modules is highlighted in the system architecture (Fig. 2). The pipeline (Fig. 3) eloquently illustrates the sequential process from input image to classification output. According to performance comparison results, the suggested model performs better in terms of accuracy, precision, and recall than conventional classifiers like SVM, Random Forest, and CNN [21], [22]. This confirms that GCN and ESBO work effectively together for medical picture analysis.

VII. Conclusion

This study offers a new method for classifying skin lesions using Enhanced Secretary Bird Optimization and Graph Convolution Networks. The suggested approach performs better by efficiently capturing spatial relationships and optimizing feature selection.

In the foreseeable future, the model will be utilized in real-time clinical applications, and explainable AI techniques will be incorporated into them.

REFERENCES

[1] M. Monajemi, "Efficiency Analysis of Convolutional Neural Networks in Multiclass Recognition of Skin Lesions via Dermoscopy Images," 10th Int. Conf. Artificial Intelligence and Robotics (QICAR), pp. 119–124, 2024.

[2] Nasr-Esfahani, "Melanoma Detection by Analysis of Clinical Images Using Convolutional Neural Network," IEEE, pp. 1373–1376, 2016.

[3] Y. LeCun et al., "Deep learning," Nature, pp. 436–444, 2015.

[4] M. Tan and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," Proc. ICML, pp. 6105–6114, 2019.

[5] D. P. Kingma and J. Ba, "ADAM: A Method for Stochastic Optimization," Proc. ICLR, 2015.

[6] L. Liu et al., "Deep Learning for Generic Object Detection: A Survey," Int. J. Comput. Vis., vol. 128, no. 2, pp. 261–318, 2020.

[7] K. He et al., "Deep Residual Learning for Image Recognition," Proc. CVPR, pp. 770–778, 2016.

[8] S. S. Han et al., "Classification of Clinical Images for Benign and Malignant Cutaneous Tumors Using Deep Learning," J. Investigative Dermatology, vol. 138, pp. 1529–1538, 2018.

[9] B. Sahiner et al., "Deep Learning in Medical Imaging and Radiation Therapy," Med. Phys., vol. 46, pp. e1–e36, 2018.

[10] A. Esteva et al., "Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks," Nature, 2017.

[11] S. Ioffe and C. Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift," Proc. ICML, 2015.

[12] B. Yu et al., "Skin Disease Segmentation Network Based on Multi-Scale Channel Attention," Comput. Methods Biomech. Biomed. Eng. Imaging Vis., vol. 11, no. 3, 2023.

[13] L. Song et al., "Decoupling Multi-Task Causality for Improved Skin Lesion Segmentation and Classification," Pattern Recognition, vol. 133, 2023.

[14] R. Mahum and S. Aladhadh, "Skin Lesion Detection Using Hand-Crafted and DL-Based Features Fusion and LSTM," Diagnostics, vol. 12, no. 12, 2022.

[15] M. A. Khan et al., "Normal Distribution-Based Segmentation and Entropy-Controlled Feature Selection for Skin Lesion Detection," BMC Cancer, vol. 18, 2018.

[16] M. A. Khan et al., "Multi-Class Skin Lesion Detection via Teledermatology," IEEE J. Biomed. Health Inform., vol. 25, no. 12, 2021.

[17] F. Afza et al., "Hierarchical Three-Step Superpixels and Deep Learning Framework for Skin Lesion Classification," Methods, vol. 202, 2022.

[18] Q. Guo et al., "Robust Fusion for Skin Lesion Segmentation of Dermoscopic Images," Front. Bioeng. Biotechnol., vol. 11, 2023.

[19] S. Maqsood and R. Damaševičius, "Multiclass Skin Lesion Localization and Classification Using Deep Learning-Based Features Fusion," Neural Netw., vol. 160, 2023.

[20] M. A. Khan et al., "Skin Lesion Segmentation and Classification Using Improved Moth Flame Optimization," Diagnostics, vol. 11, no. 5, 2021.

[21] M. A. Khan et al., "Intelligent Fusion-Assisted Skin Lesion Localization and Classification," Neural Comput. Appl., vol. 36, 2024.

[22] A. Bibi et al., "Skin Lesion Segmentation and Classification Using Conventional and Deep Learning Framework," Comput. Mater. Continua, vol. 71, no. 2, 2022.